

# Investigation of Cue-based Aggregation in Static and Dynamic Environments with a Mobile Robot Swarm

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### Abstract

Aggregation is one of the most fundamental behaviors that has been studied in swarm robotic researches for more than two decades. The studies in biology revealed that environment is a preeminent factor in especially cue-based aggregation that can be defined as aggregation at a particular location which is a heat or a light source acting as a cue indicating an optimal zone. In swarm robotics, studies on cue-based aggregation mainly focused on different methods of aggregation and different parameters such as population size. Although of utmost importance, environmental effects on aggregation performance have not been studied systematically. In this paper, we study the effects of different environmental factors; size, texture and number of cues in a static setting and moving cues in a dynamic setting using real robots. We used aggregation time and size of the aggregate as the two metrics to measure aggregation performance. We performed real robot experiments with different population sizes and evaluated the performance of aggregation using the defined metrics. We also proposed a probabilistic aggregation model and predicted the aggregation performance accurately in most of the settings. The results of the experiments show that environmental conditions affect the aggregation performance considerably and have to be studied in depth.

**Keywords:** Swarm Robotics, Aggregation, Collective Behavior, Cue-based aggregation

# 1 Introduction

Environment plays a crucial role in the daily routine and life cycle of all animals. Animals, their nests, behaviors and nutrition habits cannot be thought independent of the environment they live in. When we consider social animals such as ants, bees and termites environment becomes even more important in their daily routine. All the decisions they make are based on social interactions with their nest-mates and the state of the environment (Amé, Halloy, Rivault, Detrain, & Deneubourg, 2006). Environment also serves as a medium for intraspecific communication (stigmergy) that is known to be a very effective way of communication in unstructured and complex environments (Schmickl & Crailsheim, 2004).

Aggregation is a widely observed phenomenon in social animals especially in social insects (Grünbaum & Okubo, 1994). It can be defined as gathering of individuals into a single aggregate at a particular location. Aggregation behavior can be observed from amoeba (Rappel, Nicol, Sarkissian, Levine, & Loomis, 1999) to insects and to other animals (Camazine et al., 2001). Animals in an aggregate gain additional capabilities such as forming a spore-bearing structure by slime mold (Bonner, 1944), building a nest by termites (Parrish & Edelstein-Keshet, 1999) or protection against predators (Johannesen, Dunn, & Morrell, 2014; Morrell & James, 2008).

Two different types of aggregation mechanisms are observed in nature: cue-based and self-organized (Camazine et al., 2001). In cue-based aggregation, animals aggregate on an external cue that is known to be an optimal zone for their survival; such as high temperature or high humidity zone for flies (Frank, Jouandet, Kearney, Macpherson, & Gallio, 2015). Self-organized aggregation does not require any external cues. Animals aggregate on some locations without any particular preference to their environmental conditions (Garnier, Gautrais, Asadpour, Jost, & Theraulaz, 2009).

Cue-based and self-organized aggregation have been studied in swarm robotics for more than two decades (Şahin, Girgin, Bayındır, & Turgut, 2008; Brambilla, Ferrante, Birattari, & Dorigo, 2013; Bayındır, 2016). In cue-based aggregation, which is the main topic of this paper, one of the seminal works is due to Schmickl et al. (Schmickl, Thenius, et al., 2009). Inspired by honeybee aggregation in which bees aggregate on optimal temperature zones (Heran, 1952), Kernbach et al. (Kernbach, Thenius, Kernbach, & Schmickl, 2009) proposed a method known as BEECLUST for robot swarms. In BEECLUST, robots perform a random walk, and after a collision with another robot, they wait for a particular amount of time directly proportional to the intensity of the light

in the environment and then they continue doing a random walk. Many robots encountering with many others cause the swarm to aggregate on the optimal zone defined by the intensity of the light. Follow up works on BEECLUST mainly focused on: (1) modifications of parameters of BEECLUST to improve its performance (Arvin, Samsudin, Ramli, & Bekravi, 2011; Arvin, Turgut, Bellotto, & Yue, 2014), (2) derivation of simpler aggregation models based on systematic honeybee experiments (Schmickl & Hamann, 2011), (3) fuzzy-based aggregation methods for better aggregation performance (Arvin, Turgut, Bazyari, et al., 2014; Arvin, Turgut, & Yue, 2012), and (4) heterogeneity in behaviors (Kengyel et al., 2015).

Although of utmost importance, to the best of our knowledge little has been done to study the effects of environment on aggregation. In this paper, we present a detailed study on effects of environmental changes on performance of a swarm system. We investigate different types of environments – static and dynamic – to check the influence of the changes on the performance of the bio-inspired aggregation mechanism based on the state-of-the-art BEECLUST algorithm.

## 2 Related Work

Study on honeybees’ thermotactic aggregation behavior is an early work on aggregation in biology (Heran, 1952) which showed that young honeybees tend to aggregate at an optimal zone with temperature between  $34^{\circ}$  and  $38^{\circ}\text{C}$  in a hive. The study revealed that bees follow a simple mechanism to form an aggregate based on two phases: performing a random walk until another bee is encountered and when encountered waiting for a certain amount of time based on the ambient temperature. Szopek et al. (Szopek, Schmickl, Thenius, Radspieler, & Crailsheim, 2013) studied the collective decision making of honeybees, which leads to thermotaxis-based aggregation at the optimal zone in a hive with a more systematic way. Their study revealed that a large group can find an optimal zone faster than the small size swarm. The results also showed that the group behavior is scalable and robust.

In another study (Raveh, Vogt, Montavon, & Kölliker, 2014), Raveh et al. showed that earwigs (*Forficula auricularia*) prefer to form aggregates with their relatives rather than other earwigs. This behavior helps to reduce the risk of competition between the individuals. In another interesting study (Broly, Devigne, Deneubourg, & Devigne, 2014), Broly et al. showed that aggregation helps woodlice colony (*Isopoda: Oniscidea*) to reduce water loss hence increase the survival rate of the colony. In case of mammals, a recent study on sea lions (Liwanag, Orazel, Costa1, & Williams,

2014) revealed that sea lions tend to gather and form an aggregate when the ambient temperature reaches critical values. Aggregation helps them to decrease the heat transfer rate, hence keep their body temperature at the optimal level with lower energy loss. Therefore, during cold seasons, most of lions join the aggregate tightly instead of resting alone. Jeanson et al. studied cockroach (*Blattella germanica*) aggregation in a homogeneous environment (Jeanson et al., 2005). They showed that the probability of a cockroach to stop and wait in an aggregate depends on the size of aggregate. The bigger it is, the longer the waiting time is. On the contrary, Amé et al. (Amé et al., 2006) studied cockroach aggregation in a heterogeneous environment. Using two identical plastic shelters in an arena, they showed that cockroaches prefer to aggregate and rest under dark shelters. They figured out that the probabilities to join and to leave an aggregate are low when the population of the shelter is large. Although, this seems contrary to Jeanson et al. (Jeanson et al., 2005), it is not. In fact, larger aggregate reduces the probability of having access to the cue, hence this forms a negative feedback mechanism.

In swarm robotics (Brambilla et al., 2013), self-organized aggregation has been performed in various studies. Trianni et al. (Trianni, Groß, Labella, Şahin, & Dorigo, 2003) presented an aggregation behavior using artificial evolution in two different settings: *static* and *dynamic*. In the static setting, when robots form an aggregate, they are not allowed to leave it, whereas in the dynamic setting, robots are allowed to leave the aggregate and join the other aggregates in the environment. In the static setting, it is observed that increasing the population size can result in formation of many separate aggregates. In the latter setting, robots in smaller aggregates have the chance to leave them and join the other ones, which finally results in formation of a single large aggregate. In another study, Soysal and Şahin (Soysal & Şahin, 2005) proposed a probabilistic aggregation mechanism based on simple behaviors as: obstacle avoidance, approach to an aggregate, repel from an aggregate, and wait. Performance of the system was investigated using various parameters including control strategies, time, and arena configuration. In a follow-up work (Soysal, Bahçeci, & Şahin, 2007), they also studied these parameters in aggregation using artificial evolution. In another study, Halloy et al. (Halloy et al., 2007) studied the aggregation behavior of a mixed group of robots and cockroaches in a two-shelter arena. The results revealed that the mixed group aggregated under the darkest shelter as expected. In a similar study, Garnier et al. (Garnier et al., 2008, 2009) used a miniature robot platform and implemented the behavioral model of cockroaches as proposed in (Jeanson et al., 2005). They were able to mimic the

aggregation behavior of cockroaches with robots in similar experimental settings as in (Jeanson et al., 2005). Campo et al. (Campo, Garnier, Dédriche, Zekkri, & Dorigo, 2011) proposed a collective decision making mechanism, which is based on the behavior of cockroaches, to discriminate between two different *quality* sources. The aim of the robots is to find the source that is the smallest, yet that can encapsulate the whole swarm. The experiments showed that the swarm was able to aggregate at the optimal source location and an increase in population size improved the performance of the swarm. In a recent study, Gauci et al. (Gauci, Chen, Li, Dodd, & Groß, 2014) proposed a self-organized aggregation mechanism with memory-less mobile robots with a binary sensor. The control mechanism includes: i) rotating on a spot when there is another robot and ii) circular backward movement when no other robot is detected. The results of simulated and real robot experiments showed that, robots tend to make a single aggregate using the proposed simple mechanism. However, to accomplish aggregation, the the binary sensor had to be able to detect other robots at a long range.

Kube and Zhang (Kube & Zhang, 1993) have performed one of the earliest studies in cue-based aggregation in swarm robotics. They proposed a collective transport scenario in which robots first aggregate around an object with a light source, and then push that object together. The aggregation method, which was used in that study is based on simple behaviors and does not rely on any explicit communication. To control the size of an aggregate in a cue-based aggregation scenario, Holland and Melhuish (Holland & Melhuish, 1997) proposed a mechanism, in which robots first aggregate around an infra-red transmitter, and then start to emit sound both synchronously and randomly. Therefore, each robot is able to estimate the aggregate size using the sound signal strength and decide to join and leave the aggregate accordingly. Mermoud et al. (Mermoud, Matthey, Evans, & Martinoli, 2010) used aggregation in a cue-based setting to enable a collective decision mechanism. Using a probabilistic aggregation method similar to the one in (Soysal & Şahin, 2005), robots first aggregate on a spot that could be either a bad spot (meaning that it should be destroyed) or a good spot (meaning that nothing should be done) and then they decide collectively whether to destroy or keep the spot intact. They showed that aggregation helps the robots to interact and communicate, which in turn helps them to make correct decisions under uncertainty due to noisy sensing. Francesca et al. (Francesca, Brambilla, Trianni, Dorigo, & Birattari, 2012) implemented the decision making strategy which cockroaches use in finding a resting shelter when there are more than one. They used a similar experimental setup which was

proposed in (Amé et al., 2006). The results showed that, the probability of leaving an aggregate relies on the population and the capacity of the shelter. In a recent study (Schmickl & Hamann, 2011), Schmickl and Hamann worked on the aggregation of young bees as in (Heran, 1952) in a more systematic way. The results of real bee and robot experiments showed that bees follow a very simple set of behaviors for aggregation as: (i) A bee performs correlated a random walk. (ii) When a bee hits a wall, it avoids the wall and then continues to perform a random walk. (iii) When a bee encounters another bee, it stops and waits for a certain amount of time. Waiting time is directly proportional to the temperature of the spot. When the waiting time is over, the bee continues to perform a random walk.

In another study (Kernbach et al., 2009), Kernbach et al. proposed an aggregation method called *BEECLUST*, which is based on honeybee aggregation as in (Schmickl & Hamann, 2011). The algorithm is based on robot-to-robot collisions as opposed to bee-to-bee encounters. In their setting, they assumed that there is a light source in the environment, which is used to create a light gradient. Robots are required to aggregate on the zone where the intensity of the light is the highest. Each robot performs a random walk and stops when it encounters another robot. The waiting time of the robot depends on the intensity of the light where it stopped. The more the intensity, the longer it waits. After the waiting time is over, the robot turns to a random direction and restarts to perform a random walk. Through experiments they showed that robots are able to aggregate on the optimal zone. In a follow-up study (Schmickl, Thenius, et al., 2009), Schmickl et al. proposed two types of experiments. One is the *static* experiments in which there is a single light source as in (Kernbach et al., 2009) and the other is the *dynamic* experiments in which there are two light sources with different intensities and the intensities of the sources are changed during an experiment. Through systematic experiments, they showed that as in (Kernbach et al., 2009), robots were able to aggregate on the optimal zone in static experiments. Whereas, in dynamic experiments, robots are able to aggregate close to the highest intensity source and when the intensities of the two sources are switched during the experiment, robots are able to leave the previously formed aggregate and form a new aggregate under the recent optimal zone.

Previously, we studied the effects of the different interactions among a group of robots and their decision making strategies. In (Arvin et al., 2011), we proposed two modifications on *BEECLUST* in order to increase its performance. One is the *dynamic velocity* in which robots are allowed to select three different speeds based on intensity of light; higher intensity results in slower speed

and vice versa. The other modification is the *comparative waiting time*. The waiting time of a robot increases in the presence of the other robots or aggregates. Both simulation-based and real robot experiments were conducted and results showed that both methods improve aggregation performance. In addition, we studied the effects of turning angle and its calculation methods on the performance of the swarm aggregation (Arvin, Turgut, Bellotto, & Yue, 2014). In that study, we compared the performance of two proposed aggregation algorithms – vector averaging and naïve – with BEECLUST. The results showed that the proposed strategies outperform BEECLUST method due to additional environmental perception. In a recent study (Arvin, Turgut, Bazyari, et al., 2014), we introduced a fuzzy-based decision making mechanism in swarm aggregation and showed that the proposed method significantly improves the performance of aggregation using real-robot and computer-based simulations (Arvin et al., 2012).

The rest of this paper is organized as follows. In Section 3, we introduce the aggregation method. Following that in Section 4, we introduce the proposed probabilistic model. In Section 5, we explain the realization of aggregation with real robots. In Section 6, we discuss the different experimental configurations and different experimental settings. In Section 7, we discuss results of the experiments in different settings. Finally, in Sections 8 and 9, we discuss the future research directions and make a conclusion of the study.

### 3 Aggregation Method

We use the state-of-the-art BEECLUST method (Schmickl, Thenius, et al., 2009). Fig. 1 shows the flowchart of the aggregation method. In this method, a robot moves forward continuously in the environment. When it encounters an object, it checks whether the object is an obstacle or another robot. If it is an obstacle, the robot avoids the obstacle and continues to move forward. If not, it stops and waits for a particular amount of time, the waiting time,  $w(t)$ . The waiting time is a function of the ambient light intensity (Schmickl, Thenius, et al., 2009), which is estimated by the following formula:

$$w(t) = \frac{60S(t)^2}{S(t)^2 + 5000} , \quad (1)$$

where  $S$  is the illuminance captured by the light sensor varying linearly from 0 and 255 corresponding to 0 lux and 600 lux. After the waiting time is over, the robot rotates  $\phi$  degrees and continues



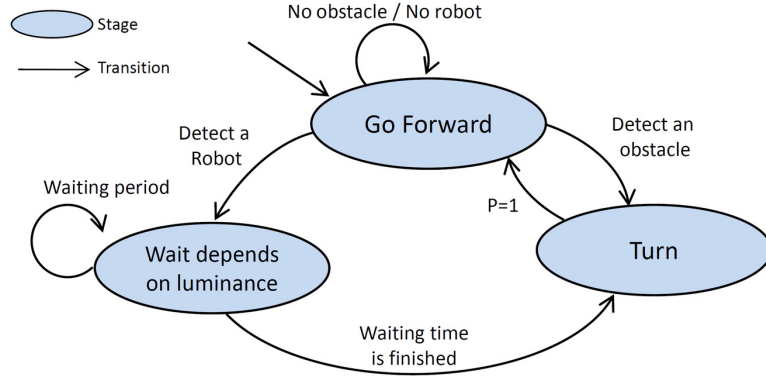


Figure 1: Finite state automaton that shows the robots' behavior in BEECLUST.

to move forward.  $\phi$  is a random variable drawn from a uniformly distributed set of angles in the range  $[-180^\circ, 180^\circ]$ .

## 4 Probabilistic Modeling of Aggregation

Stochastic characteristic of aggregation induce to use a probabilistic modeling scheme. To this end, several probabilistic models have been proposed in swarm robotics (Martinoli, Ijspeert, & Mondada, 1999; Lerman, Galstyan, Martinoli, & Ijspeert, 2001; Correll & Martinoli, 2007). Soysal and Şahin (Soysal & Şahin, 2007) proposed a macroscopic model of an aggregation behavior, which is able to predict the final distribution of the system. Bayındır and Şahin (Bayındır & Şahin, 2009) proposed a macroscopic model for a self-organized aggregation using probabilistic finite state automata, which could depict the behavior of swarm system appropriately. Hamann (Hamann, 2008) modeled the collective behavior of robots in a cue-based aggregation using a Langevin equation. Schmickl et al. (Schmickl, Hamann, Worn, & Crailsheim, 2009) proposed a macroscopic modeling of the cue-based aggregation using *Stock & Flow* model. In our previous work (Arvin, Attar, Turgut, & Yue, 2015), we proposed a mathematical model using a power-law equation to predict the aggregate size over time.

In this work, to model the influence of the environmental parameters on the swarm behavior, we use a rate equation that represents the three processes that influence the size of an aggregate in single cue experiments. The equation is based on the probabilities of individual robots joining and leaving the aggregate during a given time interval. The rate of change of the number of aggregated

robots,  $n_a$ , can be expressed by means of these probabilities as:

$$\dot{n}_a = \frac{dn_a}{dt} = n_f(2p_m + p_j) - n_a p_l \quad , \quad (2)$$

where  $p_j$  is the probability that a robot joins the aggregate,  $p_m$  represents the probability that two non-aggregated robots meet on the cue,  $p_l$  represents the chance that an aggregated robot leaves the aggregate and  $n_f$  is the number of non-aggregated (free) robots. To calculate  $p_j$  and  $p_m$ , we have to find the chance that one robot detects another one during a given time interval. We based our approximation on an area that a single robot sweeps during a unit of time. Given that radius of the sensory system is  $r_s$  and the robot radius is  $r_r$ , two robots detect each other if their centers become closer than  $r_s + r_r$ . This means that during one second of movement with a speed of  $v_r$ , a robot sweeps an area equal to  $a_s = (r_s + r_r) v_r$ . Given that the density of the non-aggregated robots excluding the subject robot is homogeneous and equal to  $(n_f - 1)/a_a$ , we can calculate the probability  $p_m$  that two non-aggregated robots meet on the cue as:

$$p_m = a_s \frac{n_f - 1}{a_a} \frac{a_c}{a_a} = (n_f - 1) \frac{a_c a_s}{a_a^2} \quad , \quad (3)$$

where  $a_c$  is the area of the cue and  $a_a$  is the area of the arena.

Similarly, we can calculate a probability  $p_j$  that a non-aggregated robot meets an aggregated one as:

$$p_j = a_s \frac{n_a}{a_c} \frac{a_c}{a_a} = n_a \frac{a_s}{a_a} \quad , \quad (4)$$

where  $n_a$  is the number of aggregated robots, the  $n_a/a_c$  is the density of the robots on the cue and  $a_c/a_a$  equals to the probability that the given robot is on the cue.

To roughly estimate a probability that a robot leaves the aggregate, we take into account the waiting time  $w$  and the chance that it will not encounter another aggregated robot on the cue while leaving as:

$$p_l = \frac{1}{2w} \left( 1 - \frac{n_a a_s}{a_c} \frac{r_c}{2v_r} \right), \quad (5)$$

where  $r_c/(2v_r)$  represents an average time it takes to leave the cue. A robot is also assumed to leave the aggregate when the dynamic cue on which the robots aggregated moves away. This means that the probability  $p_l$  is increased by the chance that a robot has been in an area that the cue

left, leading to:

$$p_l = \frac{1}{2w} \left( 1 - \frac{n_a a_s r_c}{a_c 2v_r} \right) + \frac{v_c}{\pi r_c} \quad (6)$$

where  $v_c$  is the velocity of the dynamic/moving cue (see Section 6.2) and  $r_c$  is its radius. Combining equations (3,4,6) allows us to express Eq.(2) as:

$$\dot{n}_a = n_f \frac{a_s}{a_a} (2(n_f - 1) \frac{a_c}{a_a} + n_a) - \frac{n_a}{2w} \left( 1 - \frac{n_a a_s r_c}{2 a_c v_r} \right) - \frac{n_a v_c}{\pi r_c}. \quad (7)$$

Taking into account that  $n_f + n_a = n$ , the rate of change  $\dot{n}_a$  can be fully expressed as a function of  $n_a$ , which allows us to calculate how the number of aggregated robots would change over time. Thus, it can be used to estimate the influence of certain parameters on the swarm behavior. Since a full analytic solution of this equation is beyond the scope of this paper, we created a Simulink model shown in Fig. 13 (see Appendix A) that allows us to change the model's parameters and study their influence qualitatively.

The proposed probabilistic model suggests that the rate at which the swarm aggregates increases quadratically with the population size: this means that a swarm with  $3n$  robots would aggregate 9 times faster than a swarm with  $n$  robots. On the contrary, the area of the cue  $a_c$  would have rather limited impact in the cue aggregation speed, because it mainly influences the aggregation speed in the initial phases, where  $p_m \gg p_j$ . The model also suggests that increasing the sensor range  $r_s$  and robot speed  $v_r$  will both affect (through the  $a_s$ ) the aggregation speed in a (linearly) proportional way. In large populations, increasing or decreasing the waiting time should affect the steady number of the aggregated robots only marginally since the chance of a robot escaping the aggregate is low.

## 5 Implementation of Aggregation

### 5.1 Robot Platform

We use Colias (Arvin, Murray, Zhang, & Yue, 2014) as our robotic platform in our experiments. It is specially designed for swarm applications. It is a small yet capable robot with a diameter of 4 cm. Colias is a compact version of AMiR (Autonomous Miniature Robot) (Arvin, Samsudin, & Ramli, 2009) with several additional functions enabling the implementation of wide range of swarm behaviors. Fig 2 shows a Colias robot and its modules. The robot has two boards – upper and

lower – which have different functions. The upper board is for high-level tasks such as inter-robot communication and user programmed scenarios, however, the lower board is designed for low-level functions such as power management and motion control. Two micro DC gearhead motors and two wheels with diameter of 22 mm move Colias with a maximum speed of 35 cm/s. The rotational speed for each motor is controlled individually using pulse-width modulation (Arvin & Bekravi, 2013). Each motor is driven separately by a H-bridge DC motor driver, and consumes power between 120 mW and 550 mW depending on the load.

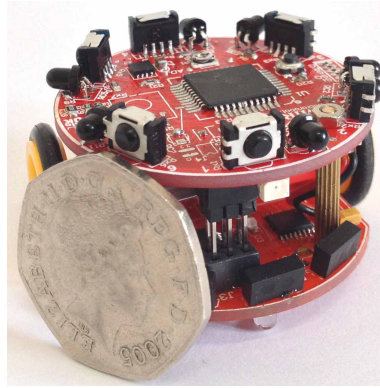


Figure 2: Colias micro mobile robot. The developed platform for swarm robotics research.

Colias uses IR proximity sensors to avoid collisions with obstacles and other robots and a light sensor to detect the intensity of the ambient light. The IR sensing system is composed of two different sub-units: The short-range sensing unit and the long range sensing unit. The short range sensing unit is composed of IR proximity sensors for immediate collision detection in a few centimeters. The long-range sensing unit is composed of six IR proximity sensors (each  $60^\circ$  on the robot's upper board). It is used for obstacle and robot detection (Arvin, Samsudin, & Ramli, 2010). It is able to distinguish robots from obstacles within approximately  $15 \pm 1$  cm. Other than these sensors, Colias has a light (illuminance) sensor at the bottom facing down, which is used to detect illuminance on the ground (this will allow us to use a horizontally placed flat LCD screen as the ground on which robots move, explained in the following section).

In Colias, the lower board is responsible for managing the power consumption as well as recharging process. Power consumption of the robot under normal conditions (in a basic arena with only walls) and short-range communication (low-power IR emitters) is about 2000 mW. However, it can be reduced to approximately 750 mW when IR emitters are turned on occasionally. A 3.7 V,



Figure 3: Arena configuration including a 42" LCD screen as the ground and a mounted camera for recording/tracking the experiments.

600 mAh (extendable up to 1200 mAh) lithium-polymer battery is used as the main power source, which gives an autonomy of approximately 2 hours for the robot.

## 5.2 Arena Setup

To realize the aggregation experiments, we use rectangular arena with size of  $90 \times 57$  cm<sup>2</sup>. We employed a horizontally positioned 42" LCD screen as the ground on which the robots move. Fig. 3 shows the arena setup. In this way, we are able to create complex experiments with different settings with ease. All the aggregation cues, we implemented, are circular light spots with maximum illuminance of 420 lux, which are controlled by a PC.

We use visual localization software developed in (Krajník et al., 2014) to track the robots during experiments using an overhead camera. To reduce the amount of collected data from the localization system, we did not record all experiments in a video. Rather than that, a image of the arena was captured every 20 seconds.

## 5.3 Metrics and Statistical Analysis

We measure the performance of aggregation using the aggregation time,  $t_a$ , and the size of the aggregate,  $n_a$  metrics. In order to define these two metrics, we need to first define the aggregation zone. The aggregation zone is defined as the area on the cue. A robot waiting on the aggregation zone is regarded an aggregated robot. The aggregation time is defined as the time that the aggregate size reaches at 70% of the total number of robots. The size of the aggregate is the total number of robots that are in the aggregate at a particular time of the experiment.

Table 1: Experimental values or range for variables and constants

Values	Description	Range / Value(s)
$n$	Population size	{9, 12, 15, 18}
$n_a$	Number of aggregated robots	0 to 18 robots
$n_f$	Number of free robots	0 to 18 robots
$S$	Sensor reading of illuminance	0 to 255
$w$	Waiting time after collision	0 to 65 sec
$v_r$	Robot forward velocity	7 cm/s
$r_s$	Radius of robot IR sensory system	$3 \pm 0.3$ cm
$r_r$	Radius of robot	2 cm
$r_c$	Radius of cue	12 to 22 cm
$a_r$	Area covered by a robot	$28 \text{ cm}^2$
$a_g$	Area covered by swarm	$170 \text{ cm}^2$ to $500 \text{ cm}^2$
$a_c$	Area of a cue	$300 \text{ cm}^2$ to $1500 \text{ cm}^2$
$a_a$	Area of the entire arena	$0.51 \text{ m}^2$
$v_c$	Motion speed of cue	{1, 5, 10} mm/s
$t$	Time	0 to 800 sec
$t_a$	Aggregate time when aggregation is accomplished	0 to 750 sec
$t_0$	Start of an aggregation scenario, $t = 0$	0
$\beta$	Ratio of the cue area to the area occupied by swarm	{2, 2.5, 3}

All results are statistically analyzed. We used analysis of variance (ANOVA) and the F-test method (Scheaffer, Mulekar, & McClave, 2010) in the analysis. F-test simply determines the degree of dependency between the selected parameters and results. A high F-value for a parameter means that it has more impact on the result.

The standard values of the constants and variables, which are used in the experiments are listed in Table 1.

## 6 Experimental Setup

### 6.1 Static Environment

In this set of experiments, we study the effects of several parameters; size, texture and number of the cue on aggregation performance in a static manner, i.e., we do not change the settings of an experiment once they are set. Each experiment is repeated with 9, 12, 15, 18 robots.

#### 6.1.1 Size of Cue

In this setting, we study the effects of the different cue sizes on the performance of aggregation using a simulated gradient light, i.e. the brightness of the cue gradually decreases from its center. We assume that  $a_r = \pi r_s^2$  is the area that a robot has a sensing radius of  $r_s$  during an instant of

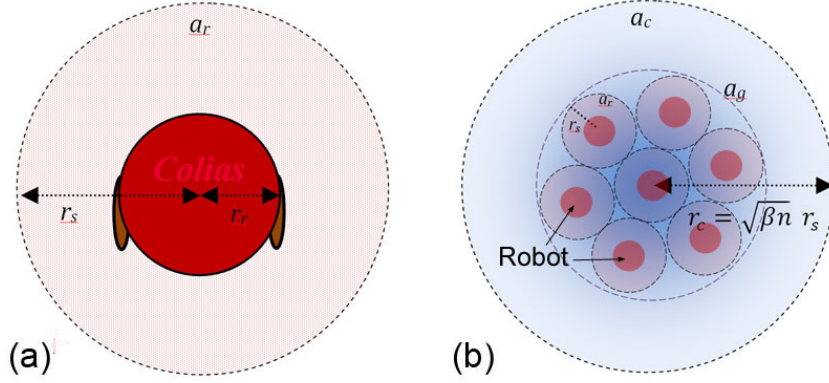


Figure 4: (a) Area,  $a_r$ , which a robot covers using its sensory system with radius of  $r_s$ . (b) A cue implemented with gradient light with an area of  $a_c$  relative to the number of robots,  $n$ , and  $\beta$ .

time (see Fig. 4a). Therefore, the total area which can be covered by radial arrangement of the robots is  $a_g = na_r$ , where  $n$  is the number of robots deployed in an experiment.

In these experiments, we use three different sizes of cue for each population size,  $a_c = \beta na_r$ ,  $\beta \in \{2, 2.5, 3\}$  (see Fig. 4b). We increase the size of the cue proportional to the population size. We set the cue sizes from a radius of 12 cm to 22 cm based on the population size and  $\beta$ . In robots,  $r_s$  is defined to be  $3 \pm 0.3$  cm hence  $a_r \simeq 28 \text{ cm}^2$ . For example, in case of 9 robots,  $a_g = 250 \text{ cm}^2$  so with  $\beta = 2$  the radius of the cue will be  $r_c = 12$  cm, or in case of 18 robots and  $\beta = 3$ ,  $a_g = 540 \text{ cm}^2$  hence the radius of cue will be about  $r_c = 22$  cm.

### 6.1.2 Texture of Cue

In these experiments, we study the effect of texture of the cue on aggregation performance. In particular, we formed two types of lighting conditions for the cue. One being the gradient type of lighting and the other being the non-gradient type of lighting. In the gradient cue, the luminance reduces gradually from the center to the edge of the cue, and in the non-gradient cue, the luminance is constant from the center to the perimeter.<sup>1</sup> For each cue type, we used two different sizes. A small cue with a radius of  $r_c = 16$  cm (1.5 times larger than the area that can accommodate 18 robots) and a large cue with a radius of  $r_c = 20$  cm (2.5 times larger than the area that can accommodate 18 robots).

<sup>1</sup>Heran et al. showed that honeybee aggregation is not only dependent on temperature itself, but also the temperature gradient around the optimal aggregation zone (Heran, 1952). In order to study this effect in our system, we change the texture, i.e., how light is distributed on the cue.

### 6.1.3 Multiple Cues

In this setting, we study the effect of multiple cues with different sizes on the aggregation performance. In this regard, we used two gradient-type circular cues having different sizes. The main cue (Zone-1 with area of  $a_{c_1}$ ) has a fixed radius of  $r_{c_1} = 16$  cm and the size of the second cue (Zone-2 with area of  $a_{c_2}$ ) is set based on the size of the main cue as:  $a_{c_2} = ka_{c_1}, k \in \{\frac{1}{3}, \frac{1}{5}\}$ . We track the size of the aggregate in both zones. Therefore, an experiment is terminated when the total number of robots (sum of all aggregate sizes) in both zones reaches 70% of the population size.

## 6.2 Dynamic Environment

In this setting, we change the position of the cue in different ways in order to create a dynamic environment. In particular, we study the adaptability of the swarm to dynamically changing environmental conditions. We created three different sets of experiments in order to test dynamic effects on aggregation performance effectively.

### 6.2.1 Switch Cue Location

In this experiment, a gradient-type cue with the radius of  $r_c = 18$  cm (which is 2 times bigger than the area that can accommodate 18 robots) is used as the aggregation zone. Each run takes 360 sec with three phases, each lasting 120 sec. This value was chosen based on the previous experiments (see Section 7.1) with similar population sizes, where the aggregation time never exceeded 120 s. In the first phase, the cue is placed on the left hand side of the arena. In the second phase of the experiment, the cue is moved instantly to the right hand side of the arena, and in the final phase the cue is moved back to the left hand side instantly. The experiment is performed with two different population sizes of 9 and 18 robots. We record the size of the aggregate during the experiments.

### 6.2.2 Delayed Motion

In this experiment, a single gradient-type circular cue with a radius of  $r_c = 18$  is used. The experiment includes two phases (stationary and moving) each lasting 120 s. In the first phase, the cue is placed on the left hand side of the arena and kept stationary and it starts to move with a



speed of  $v_c = 3.5$  mm/s continuously in the second phase.<sup>2</sup> We repeat the experiment with 12 and 18 robots and we track the size of the aggregate with a period of 20 s.

### 6.2.3 Continuous Motion

In this setting, we use a single gradient-type circular cue with a radius of  $r_c = 18$  cm, which moves in a random direction continuously with a speed of  $v_c$  mm/s,  $v_c \in \{1, 5, 10\}$ . We repeat the experiment with 9 and 18 robots. During the experiments, we track the number of aggregated robots every 20 s.

## 7 Results

The results of the experiments are presented in this section. The results are depicted as box-plots. In the box-plots, boxes show the range of the first and the third quartiles of the data. Median of the data is shown with a horizontal line inside the boxes. The whiskers show the range between the minimum and maximum values of the data.

A sample video of the swarm behavior and the experimental setup are provided online (Arvin, 2014).

### 7.1 Static Environment

Here, we depict the results of size of cue, texture of cue and multiple cues experiments.

#### 7.1.1 Size of Cue

Aggregation time with respect to different cue sizes and number of robots is depicted in Fig. 5. We can see that for a fixed size cue an increase in the number of robots decreases the aggregation time. This effect is more preeminent when the number of robots is smaller. When we keep the number of robots the same, and change the size of the cue, we observe that larger cue size results in a shorter aggregation time.

These observations are as expected. An increase in the number of robots increases the probability of collisions hence increases the probability to form an aggregate (provided that there is no

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<sup>2</sup>The reason we chose the speed is that, if a robot encounters another one at a position where the light intensity is high, the robot is going to wait for 55 s. With  $r_c = 18$  cm, we guarantee that the waiting robot will not be on the cue after the waiting time is over, since the cue has already moved 19 cm during the waiting time.

overcrowding effect). On the other hand, an increase in the size of the cue increases the probability of successful collisions (meaning that the collision happened on the cue) hence increasing the probability to form an aggregate. Both resulting in a decrease in aggregation time.

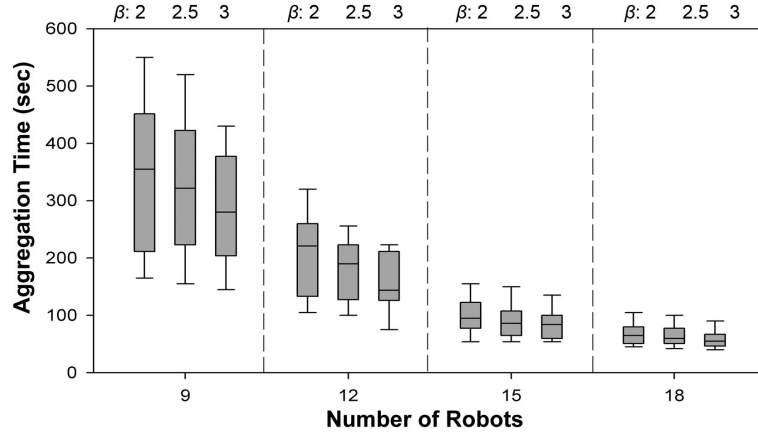


Figure 5: Aggregation time in different population sizes at different cue sizes  $\beta \in \{2, 2.5, 3\}$ .

The results of the proposed probabilistic model is depicted (shown in blue continuous line) together with size of cue results (here Fig 5 is redrawn for each  $\beta$ ) as in Fig. 6. The model is able to predict aggregation time results both qualitatively and quantitatively.

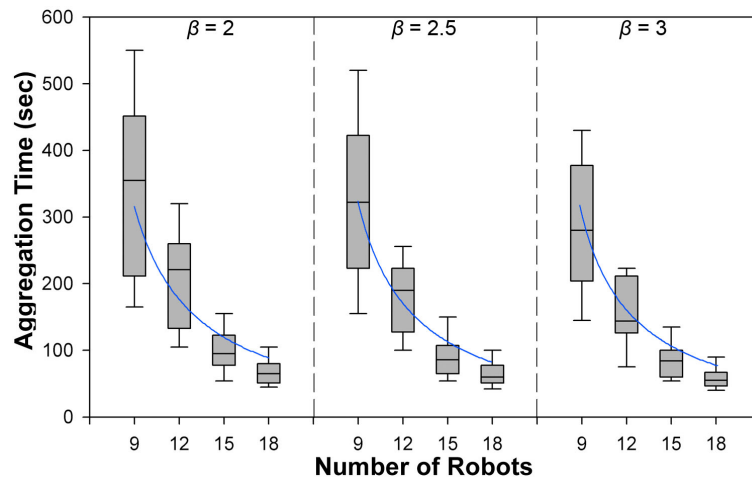


Figure 6: Aggregation time in different  $\beta$ . Continuous lines show the predicted aggregation size by the proposed model.

We analyzed the results statistically. First, we used two-way ANOVA with factors of population and cue sizes to find the most effective factor on the aggregation time. We found that, the population size has more significant influence ( $P = 0.00, F = 81.73$ ) than cue size ( $P = 0.07, F =$

2.64) on the aggregation time. We then statistically analyzed the effects of cue size on each population, separately. The results showed that, the changes in cue size affect the aggregation time more in small population than the large population ( $F = \{0.85, 0.72, 0.66, 0.51\}$  for  $n = \{9, 12, 15, 18\}$ , respectively). Therefore, increase in population size compensates the fluctuations in the cue size.

### 7.1.2 Texture of Cue

The results of the experiments with a small cue (top) and a large cue (bottom) depicted in Fig 7. The predictions of the proposed model is also depicted on the same figure as a continuous blue line. In all the experiments, increase in the number of robots reduces the aggregation time. We can also observe that aggregation times with gradient-type cue is almost the same as the non-gradient-type cue. The only exception is the higher populations (with 15 and 18 robots) with non-gradient cue, which the swarm performance reduced in comparison to the same population size with gradient cue.

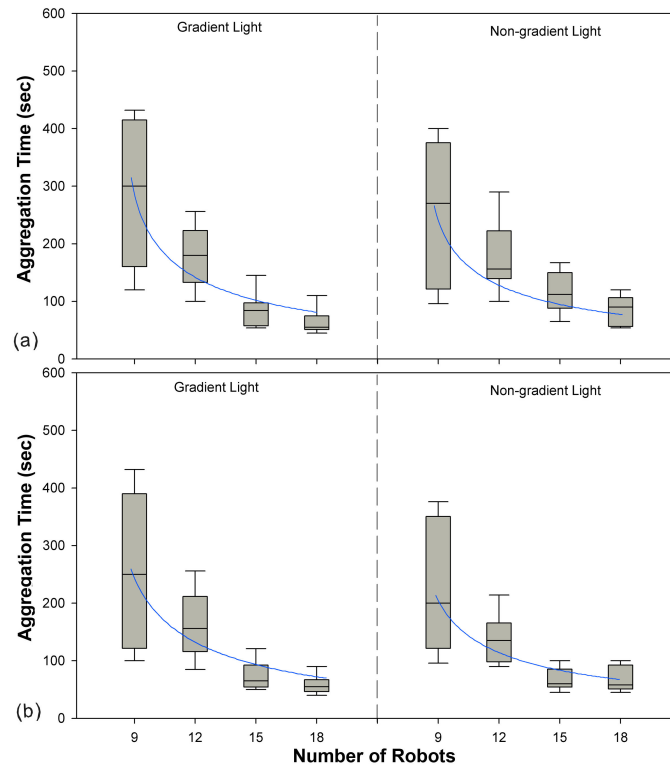


Figure 7: Aggregation time with gradient and non-gradient lights in different population sizes at (a) a small size cue (with radius of 16 cm) and (b) a big size cue (with radius of 20 cm). Continues lines indicate the predicted values from the probabilistic model.

Most of the results are in accordance with the expectations. An increase in the number of robots in any setting due to increase in the probability of collisions decreases the aggregation time. Here, we also see this effect. The type of lighting of the cue does not change the performance considerably. This was rather unexpected, but it could be due to geometrical constraints imposed by the size of robots and size of the cue. The proposed model is able to predict the results both qualitatively and quantitatively also in this case.

We also analyzed the results statistically to see how aggregation time is dependent on the different factors. We checked the effects of population and texture of the cue as the factors and the aggregation time as the response (see Table 2). The results of the statistical analysis show that, in both cue sizes, the population size has significant impact on the aggregation time. However, the texture of the cue does not have a significant impact on the performance. We also analyzed the effects of cue size and population as two independent factors. The results of the statistical analysis revealed that, the population size is more effective ( $P < 0.05$ ,  $F = 77.52$ ) than the cue size ( $P < 0.05$ ,  $F = 9.68$ ) on the performance of the swarm.

Table 2: Results of analysis of variance (ANOVA)

Cue Size	Factor	$P$ value	$F$ value
Big cue	Population	0.00	35.52
	Texture	0.20	1.62
Small cue	Population	0.00	40.66
	Texture	0.20	1.15

### 7.1.3 Multiple Cues

The results of the experiments with two different cue sizes (second cue is  $\frac{1}{3}$  or  $\frac{1}{5}$  of the area of the first cue, which has a radius of 16 cm) and different population sizes are shown in Fig. 8. We can clearly see that as in all the other experiments, an increase in the population size, decreases the aggregation time. The aggregation time with a large secondary cue (Fig. 8a) is faster than the aggregation time with the smaller secondary cue (Fig. 8b) since we are counting the total number of robots in both zones, bigger second cue means bigger total aggregation zone.

We also investigated the number of aggregated robots at both cues (Zone-1 and Zone-2) separately in varying population sizes as shown in Fig. 9. The results reveal that an increase in the population size increases the size of aggregate at the main cue (Zone-1). However, interestingly the number of the aggregated robots on the small cue (Zone-2) does not show a significant increase.

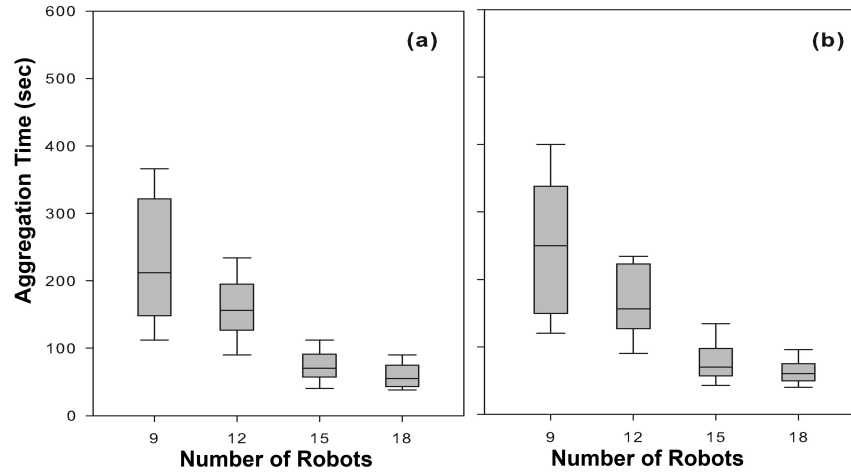


Figure 8: Aggregation time as a function of population size in (a)  $a_{c_2} = \frac{1}{3}a_{c_1}$  and (b)  $a_{c_2} = \frac{1}{5}a_{c_1}$ .

In addition, size of the second cue has an impact on the number of aggregated robots on the first cue. The number of aggregated robots increases when the size of the second cue is small.

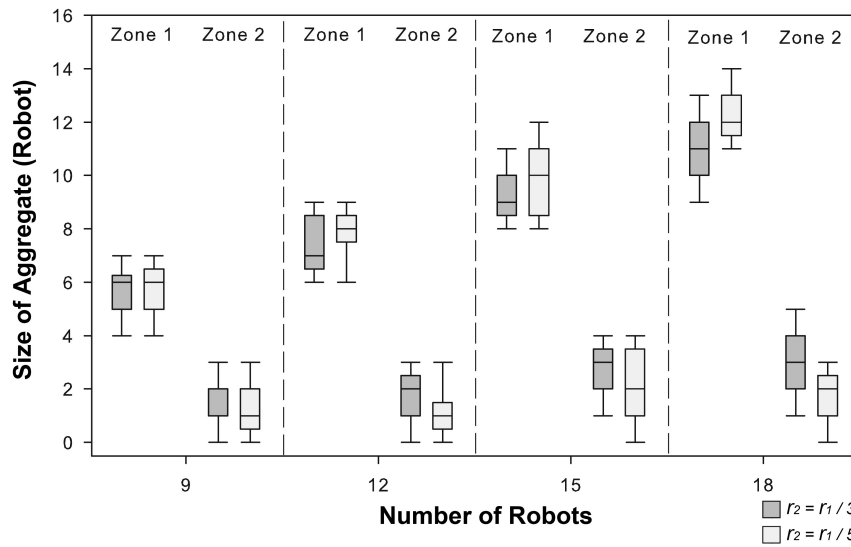


Figure 9: Number of the aggregated robots at Zone-1 (the big size cue with area of  $a_{c_1}$ ) and Zone-2 (the small size cue with area of  $a_{c_2}$ ).  $a_{c_2} = \frac{1}{3}a_{c_1}$  (the dark boxes in the diagram) and  $a_{c_2} = \frac{1}{5}a_{c_1}$  (the light boxes in the diagram).

We also statistically analyzed the results (number of robots on Zone-1 and Zone-2 tracked separately) using ANOVA two-way test (see Table 3). The analysis revealed that both population size and the size of the second cue have significant impact ( $P < 0.05$ ) on the number of robots on the first cue. In particular, the population size ( $F = 214.50$ ) influences the size of the aggregate

on the first cue more than the size of the second cue ( $F = 42.19$ ). We also analyzed the effects of population and cue size as two independent factors. The results of the statistical analysis show that, the population size has more impact ( $F = 42.81$ ) on the aggregation time than the size of the second cue ( $F = 0.54$ ).

Table 3: Results of analysis of variance for size of the aggregate

Aggregation Zone	Factor	$P$ value	$F$ value
Zone-1	Population	0.000	214.50
	Ratio of $a_{c_2}$	0.000	42.19
Zone-2	Population	0.005	4.06
	Ratio of $a_{c_2}$	0.001	11.31

## 7.2 Dynamic Environment

In this set of experiments, we study the adaptability of the aggregation method to dynamic environments.

### 7.2.1 Switch Cue Location

The time evolution of the size of the aggregate with 12 robots (top) and 18 robots (bottom) are depicted in Fig. 10. During the first 120 s, robots aggregated on the cue, which was on the left hand side of the arena. In the next 120 s, the cue was moved instantly to the right and robots rapidly adapt to the change and start to aggregate on the cue. When the cue was moved back to its original position on the left, the robots again adapted to this change and aggregated on the cue. In general, we can claim that the aggregation method tackled well with dynamically changing cue location.

### 7.2.2 Delayed Motion

The time evolution of the size of the aggregate with two different population sizes (12 robots on the left and 18 robots on the right) is depicted in Fig. 11. During the first 120 s of the experiment, most of the robots were able to aggregate on the cue. In the second phase, when the cue started to move with a constant speed, we can clearly see that number of aggregated robots decrease slowly and stabilizes around 3 robots for the 12 robots experiment and 7 for the 18 robots experiment around 180 s. We can say that the robots are not able to track a moving cue due to cue's speed (3.5 mm/s)

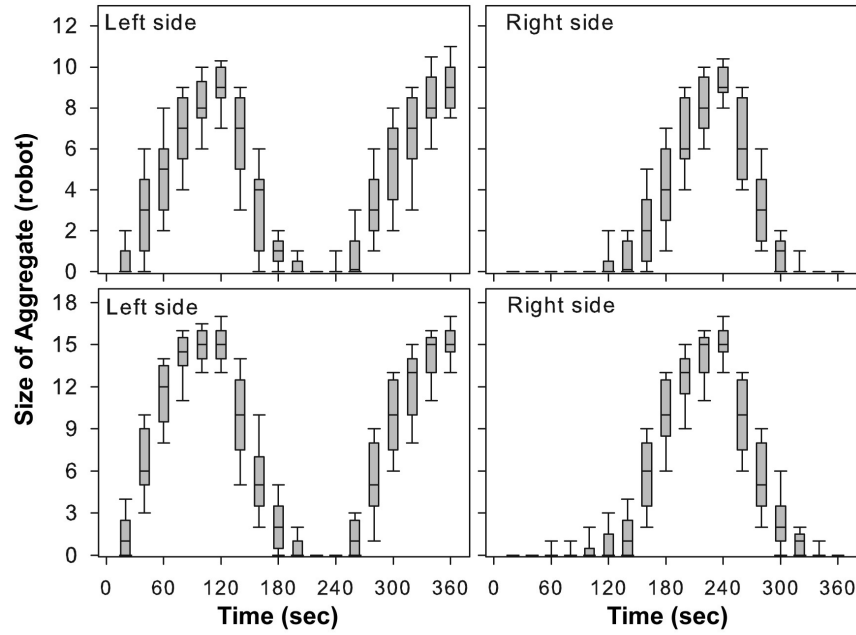


Figure 10: Size of the aggregate during experiments in dynamic environment with different population sizes ( $n \in \{12, 18\}$ ).

and high waiting times on the cue. In the next set of experiments, we can clearly see that when cue's speed is low enough (1 mm/s), robots are able to track the cue with success.

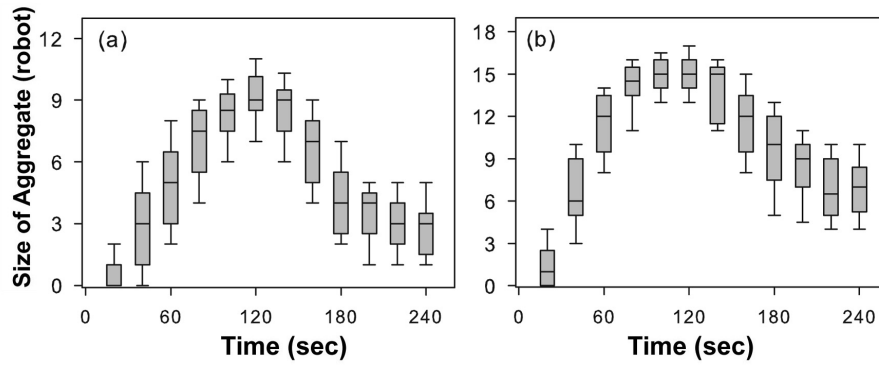


Figure 11: Size of the aggregate during experiments in dynamic environment with different populations ( $n \in \{12, 18\}$ ).

### 7.2.3 Continuous Motion

The results of the continuous motion experiment with two different population sizes (9 robots shown with empty boxes, and 18 robots shown with filled boxes) and the prediction of the model (blue continuous line) are depicted in Fig. 12. The results clearly show that the speed of the

cue, as also discussed in delayed motion experiments, affects the aggregation performance. When the speed is 1 mm/s, the robots are able to track the cue with considerable success for both population sizes. However, when the speed is 5 mm/s, the performance decreases considerably and for 10 mm/s it is even worse. These results are as expected due to cue speed and waiting time relation. With high waiting times, the robots are not able to cope with high cue speeds, so the aggregation performance is adversely affected. The model is able to predict the size of the aggregate both qualitatively and quantitatively for the two population sizes and the three speeds tested.

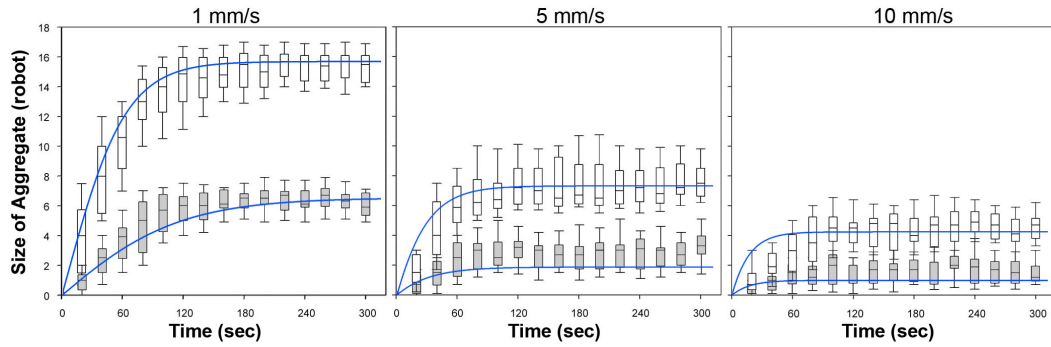


Figure 12: Size of the aggregate during experiments in dynamic environment with different cue speeds ( $v_c \in \{1, 5, 10\}$  mm/s). Filled box indicates the results with 9 robots and empty box indicates the results with 18 robots. The continuous lines show the output of model.

## 8 Discussion

The results indicated that environmental changes play a very important role in cue-based aggregation. Any change on the experimental setup changed the aggregation performance. Here, we discuss these effects in the static and dynamic configurations in detail.

### 8.1 Static Arena

Similar to the other works in aggregation (Campo et al., 2011; Arvin et al., 2011; Arvin, Turgut, Bazyari, et al., 2014), an increase in population size increases the performance of the system in the static configuration (Section 7.1) provided that the increase does not cause any interference in the system as noted in (Hamann, 2013). We prevent interference by keeping the number of robots, hence the density of robots below a certain value. Since the BEECLUST method is a collision-based algorithm, any interaction between the robots start with a collision. Increasing



the number of robots, increases the number of collisions resulting in an increase in aggregation performance. This results is in-line with the fact that increase in the number of agents in a swarm system increases the *opportunities of cooperation* as discussed in detail in (Hamann, 2013). The following observations are made about the static experiments:

- In the first experiment, we investigated the effect of the cue size on the aggregation performance (Section 7.1.1). The statistical analysis revealed that the population size has a significant impact on the performance. Other than the population size, the size of the cue is also another factor that affects the aggregation performance, which shows itself more in small populations. An increase in the size of the cue increases the probability of successful collisions (collisions on the cue) eventually increasing the performance in low population sizes. The adaptability of a swarm system to the environmental changes was also reported in (Liu, Winfield, Sa, Chen, & Dou, 2007), which is in accordance with our findings.
- In the second experiment (Section 7.1.2), we tested the effect of the texture of the cue. The aggregation times with the non-gradient and gradient cues are almost the same. Similar to the previously results, increasing the number of robots increases the performance of aggregation. However, the increase in the performance does not remain the same when the population size increases to 15 robots and more due to barrier, which is formed around the cue. Since entire cue has same luminance, in high populations the aggregate is formed nearby the edges hence the way to reach the center of the cue by the other robots is blocked. Statistical analysis of the results showed that the texture and size of the cue have less impact on the the aggregation performance than the population size.
- In the third experiment (Section 7.1.3), we investigated the effect of multiple cues on the aggregation performance. Similar to the other experiments, we first observed that an increase in population size increases the aggregation performance (Fig. 8). We also observed that a large second cue results in a higher performance increase than a smaller second cue, since a large second cue increases the aggregation area more than a smaller cue (in that setting we are counting the total number of robots on the first and second cue). Another observation is that number of robots aggregated on the first cue is more than the second cue, and this difference gets more when the population size increases (Fig. 9). This is a similar phenomenon observed in honeybee aggregation (Szopek et al., 2013) where it is observed that larger groups decide

faster on optimal temperature zones than smaller groups.

## 8.2 Dynamic Arena

We investigated the adaptation characteristics of the aggregation method by changing the environment conditions dynamically in three different experiments.

- In the first experiment (Section 7.2.1, the location of the cue moves instantly from the leftmost side of the arena to the rightmost side and then moves back to its original position. We observed that similar to the static arena experiments that larger population has higher aggregation performance, which is especially observed in the first phase of the experiments. However, at the start of the second and third phases, robots start to leave the aggregate (the cue has already moved to its next position) when the waiting time is over. Since the waiting time is only a function of light (see Eq. 1), it is not affected by the population size as much as the first phase. A similar behavior in a dynamic environment was also reported in (Liu et al., 2007).
- In the second experiment (Section 7.2.2, we evaluated the adaptability of the aggregation method using a moving cue with a constant speed. The results revealed that the aggregated robots can track the moving cue, but the aggregation performance is not as high as expected. This could be due the speed of the cue, speed of the robots and the duration of the waiting time. Adaptability of a swarm system under various environmental changes has also been studied in (Stewart & Russell, 2006).
- In the third experiment (Section 7.2.3), the cue moves to a random direction continuously with different speeds. The results showed that when the cue moves with a relatively low speed (1 mm/s), the robots can easily track the cue and aggregation performance is high. However, when the speed of the cue increases the robots start to lose the cue as discussed in the second configuration above.

## 8.3 Modeling

The probabilistic model introduced in Section 4 could predict the overall aggregation behavior both qualitatively and quantitatively to an acceptable accuracy, but still it needs to be improved. Some observations are:

- In the model it is assumed that the robots are uniformly distributed on the cue. However, especially the gradient-type cue causes the aggregated robots to concentrate in the cue center while the non-gradient type cue has most of the aggregated robots around the edge. The distribution of the robots on the cue affects both their waiting times and chances to rejoin the aggregate after their waiting time elapses. Thus, omitting this effect affects the models prediction of the probability that a robot leaves the aggregate.
- The waiting time of the robots is modeled as a probability that a robot leaves at a given time, while the robots wait for a fixed time period. Again, this impacts the model’s ability to predict the behavior of the swarm during the initial states of the aggregation.
- The model is inspired by collision modeling of gas molecules, which assumes a specific range of body-per-volume density and molecule speed. We have observed that for low population swarms (6 and below), the model predicted unrealistically long aggregations times.
- The model assumes constant robot speed, but the robots speed vary, e.g. when avoiding the arena walls. This required that the speed of the robots in the model was reduced.
- The model does not represent the effects of sensor noise: Sometimes the robots miss each other even when passing within the sensory range. To represent this effect in the model, we decreased the IR range radius  $r_s$ .
- Some of the environment effects such as the gradient light and sensor noise are difficult to represent rigorously. Thus, we have substituted their effects by parameters that had to be hand-tuned.

Despite of the aforementioned imperfections, the model is able to predict the aggregation times in environments with approximately 10% error.

## 9 Conclusion

In this paper, we investigated the performance of the state-of-the-art BEECLUST aggregation method in different environmental conditions. We observed that environment plays a very important role in aggregation performance as also observed in social animals such as ants and termites (Depickere, Fresneau, & Deneubourg, 2008). In particular, we focused on a cue-based

aggregation scenario and observed some important facts: (1) Despite all the other environmental effects, population size plays the most important role in aggregation performance. Increase in the population size increases the probability of collisions between the robots, hence increases the probability to form an aggregate on the cue. This is an expected result (Campo et al., 2011; Arvin et al., 2011; Arvin, Turgut, Bazyari, et al., 2014) provided that the number of robots (or the density) stays below a critical level in which interference (Goldberg & Mataric, 1997) starts to occur and degrades the performance (Hamann, 2013). (2) BEECLUST, or in general, a collision-based aggregation method, although being very simple, is able to distinguish between two cues (one being large and the other being small) and more robots aggregate on the larger cue than the smaller cue. This effect is observed even more with a larger population as discussed in Section 8.1. To put in another way, BEECLUST is able to discriminate between two cues (or sources) based on their size (or quality) efficiently in a self-organized way with a very simple decision-making mechanism as observed in social animals (Campo et al., 2011). (3) Adaptation ability of BEECLUST method is quite impressive as observed in dynamic environments (Section 8.2). Unlike other methods (designed purposefully to be adaptive), BEECLUST is inherently adaptive to changing environmental conditions.

As a future work we are planning to investigate the effect of density on aggregation performance. We are planning to test the extreme conditions such as very low density and very high density, and study the effect of interference on system performance using computer-based simulations. We will also study the effects of environmental changes using a heterogeneous swarm and we will look for ways to improve adaptability of the aggregation method by modifying the original method. By solving the differential equation that constitutes our model, we will obtain the aggregate size as a function of time, swarm and environment parameters. This will allow us to infer parameters of individual robots from the global swarm behavior by fitting the model to the observed data.

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## Appendix A

To be able to adjust the parameters of the probabilistic model easily while having a good overview of their influence on the swarm behavior, we have created a SIMULINK model of the Eq. 7. The model breaks down the Eq. 7 to the individual products and sums of the model parameters (robot speed, sensor range, arena dimensions, cue area) and the number of currently aggregated and non-aggregated robots. The results of the calculation, which are the rates at which the robots leave and join the aggregate, are summed and passed to the integrator block, that represents the system

state – the number of aggregated robots. In other words, the SIMULINK model is equal to the integral form of the differential Eq. 7. Fig. 13 shows the SIMULINK model.

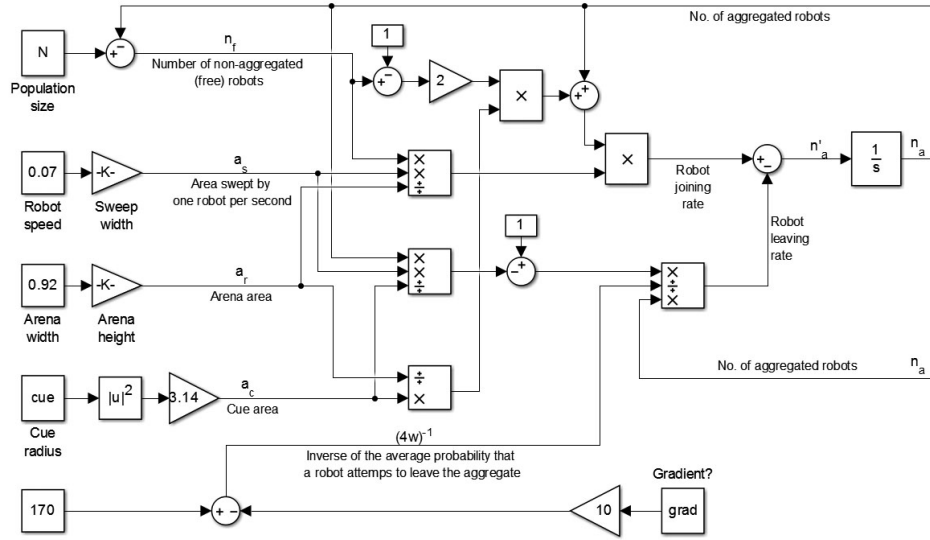


Figure 13: SIMULINK model for the probabilistic modeling of the aggregation.



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